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Using EEG to Detect and Monitor Mental Fatigue

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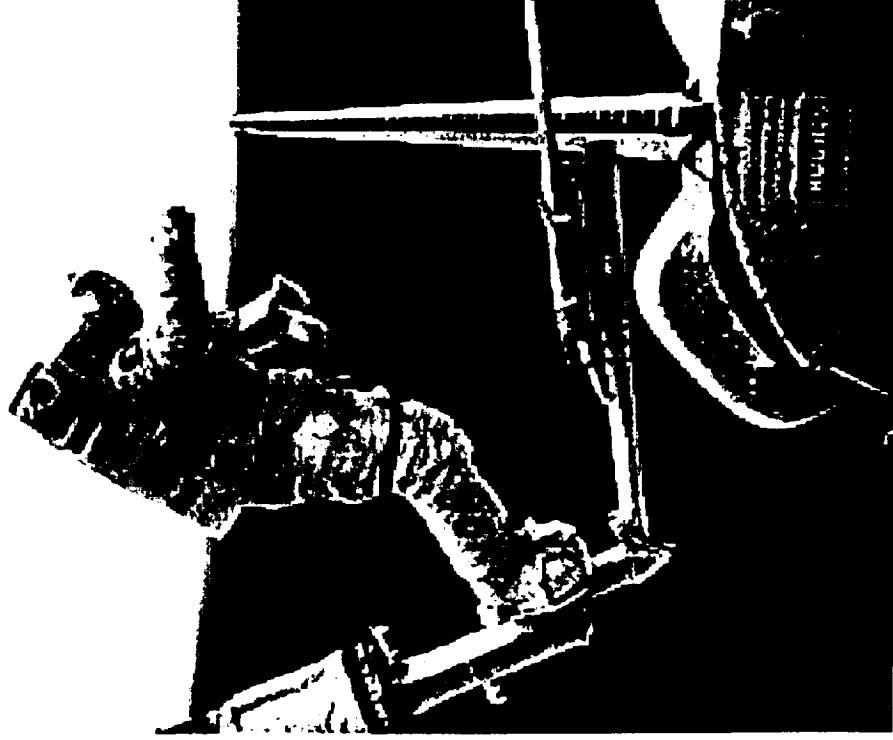
Title: USING EEG TO DETECT AND MONITOR MENTAL FATIGUE

Leslie Montgomery, Bernadette Luna, Richard Montgomery, Leonard J. Trejo

Abstract (poster presentation)

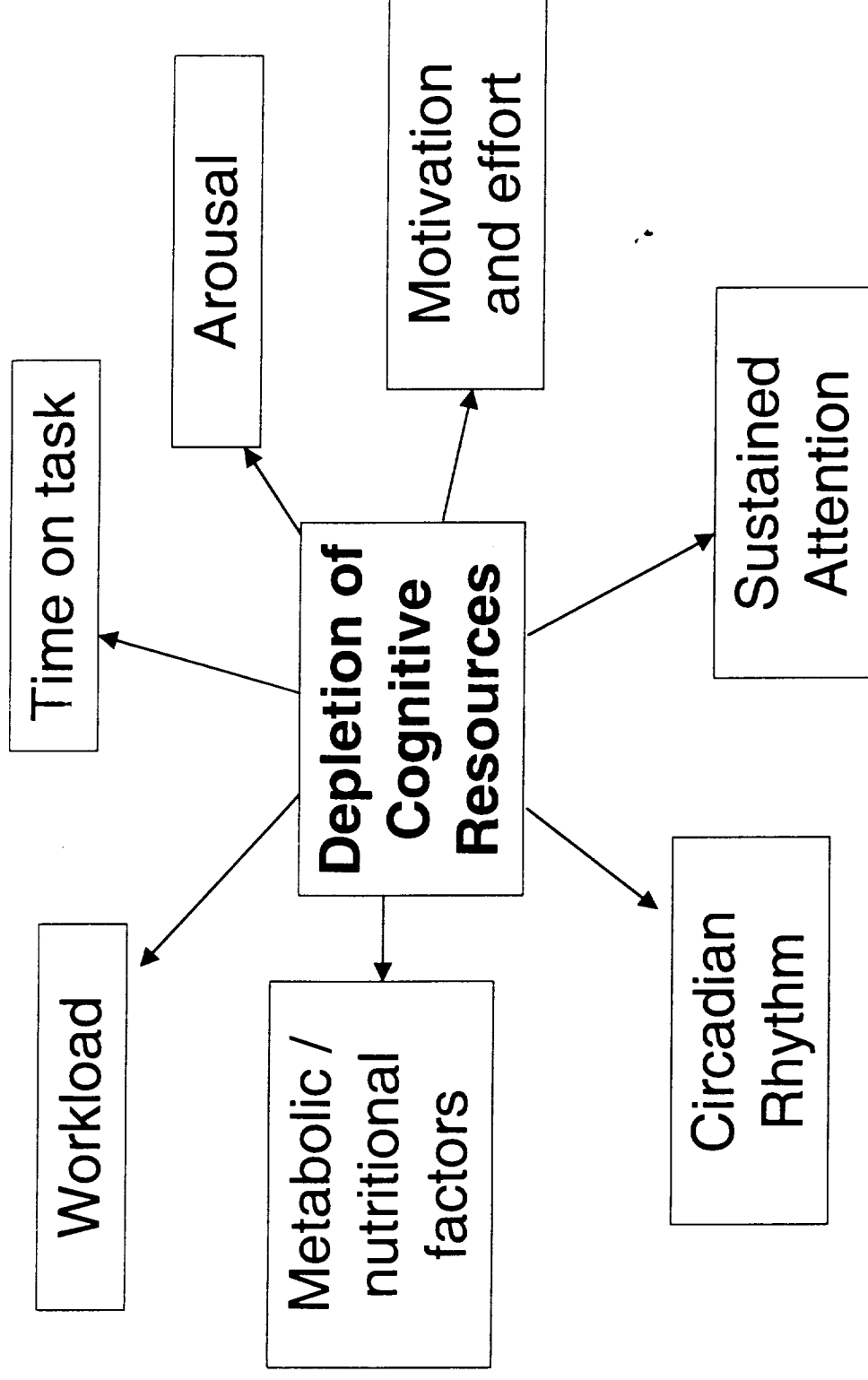
This project aims to develop EEG-based methods for detecting and monitoring mental fatigue. Mental fatigue poses a serious risk, even when performance is not apparently degraded. When such fatigue is associated with sustained performance of a single type of cognitive task it may be related to the metabolic energy required for sustained activation of cortical areas specialized for that task. The objective of this study was to adapt EEG to monitor cortical energy over a long period of performance of a cognitive task. Multielectrode event related potentials (ERPs) were collected every 15 minutes in nine subjects who performed a mental arithmetic task (algebraic sum of four randomly generated negative or positive digits). A new problem was presented on a computer screen 0.5 seconds after each response; some subjects endured for as long as three hours. ERPs were transformed to a quantitative measure of scalp electrical field energy. The average energy level at electrode P3 (near the left angular gyrus), 100-300 msec latency, was compared over the series of ERPs. For most subjects, scalp energy density at P3 gradually fell over the period of task performance and dramatically increased just before the subject was unable to continue the task. This neural response can be simulated for individual subjects using a differential equation model in which it is assumed that the mental arithmetic task requires a commitment of metabolic energy that would otherwise be used for brain activities that are temporarily neglected. Their cumulative neglect eventually requires a reallocation of energy away from the mental arithmetic task.

Some Health Hazards in Long-Duration Missions



- Cephalad Fluid Shifts/Loss
 - Orthostatic intolerance upon reentry
 - Venous thrombosis
- Bone Demineralization
 - Fractures
 - Kidney stones
- Muscle Atrophy
 - Loss of strength
- Cardiovascular Deconditioning
 - Heart problems
 - Hypertension
- Isolation/Confinement/Stress
 - Neurobehavioral dysfunction
- Repetitive Motion Syndrome

Cognitive Fatigue



Previous Research

Multiple Sclerosis

- Evidence of EEG energy density correlations (Montgomery et al.)
- Krupp & Elkins (2000) - declines in single session

Lyme Disease

- Pollina et al. (1999) - cognitive deficits in speeded tasks, not seen in controls or depressed patients

Extended Wakefulness: ERP & Performance Studies

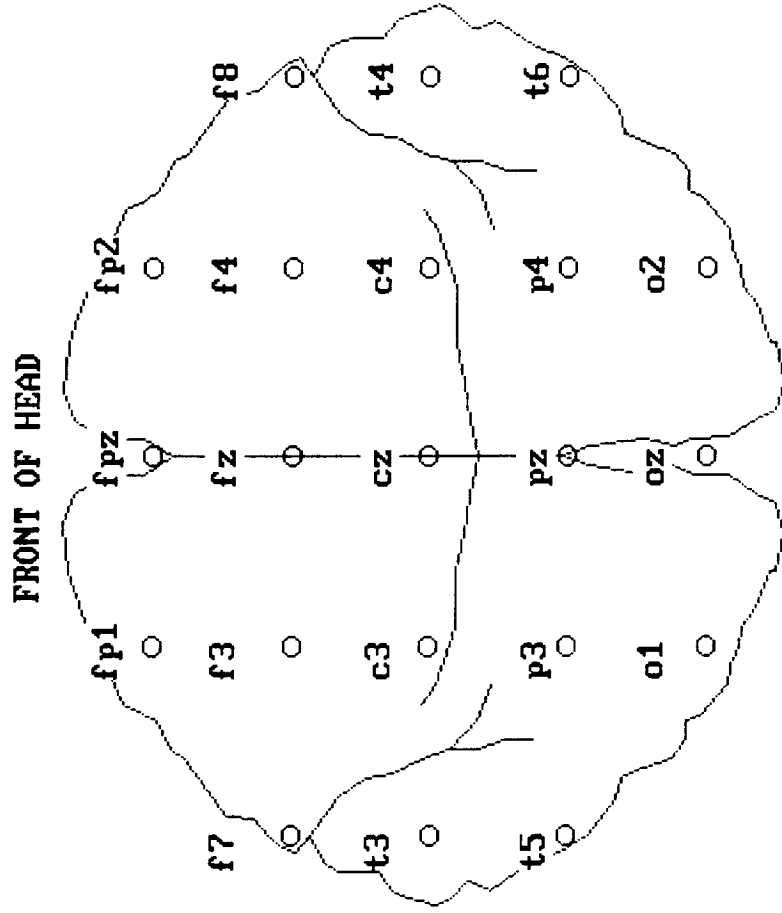
- Declines in early perceptual processes -- Humphrey, Kramer & Stanny (1994)
- Decreased effectiveness of error detection processes (Scheffers et al. 1999)

Mental Arithmetic Task

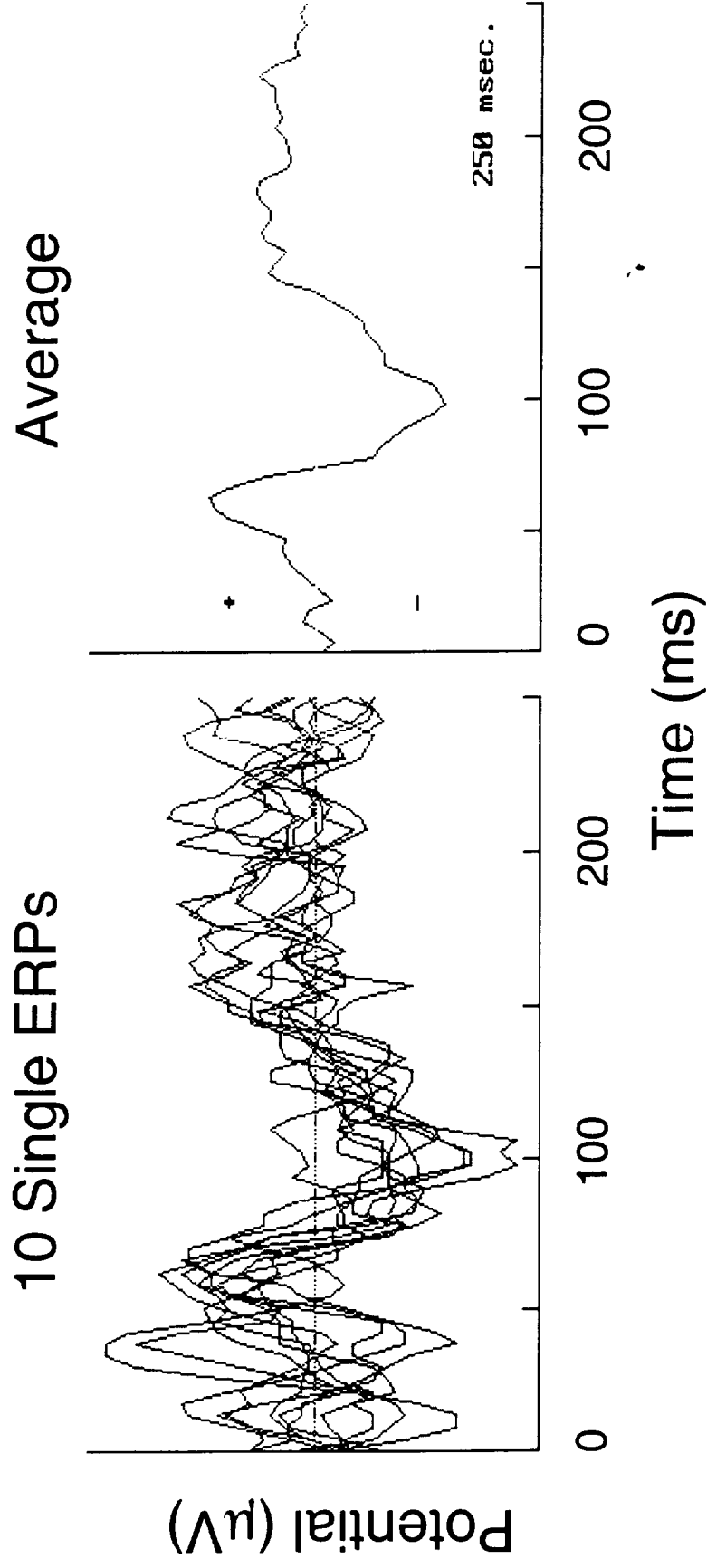
$$+1 - 5 + 6 + 9$$

$$\langle = \rangle \quad 11?$$

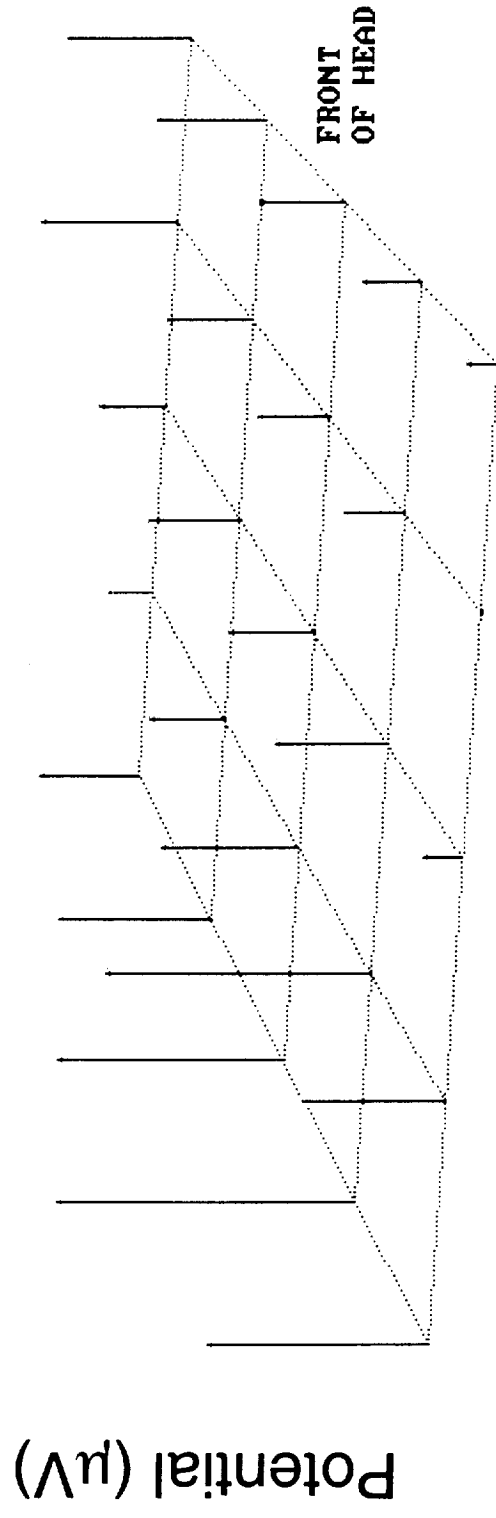
Electrode Locations



Sample Single and Averaged ERPs



Sample EEG Surface Potential Distribution



2-D Projection of Electrode Location

Surface-Fitting Equation for Potentials

V = potential at electrode coordinates X, Y

X = side-to-side direction in 2-D projection

Y = front-to-back direction in 2-D projection

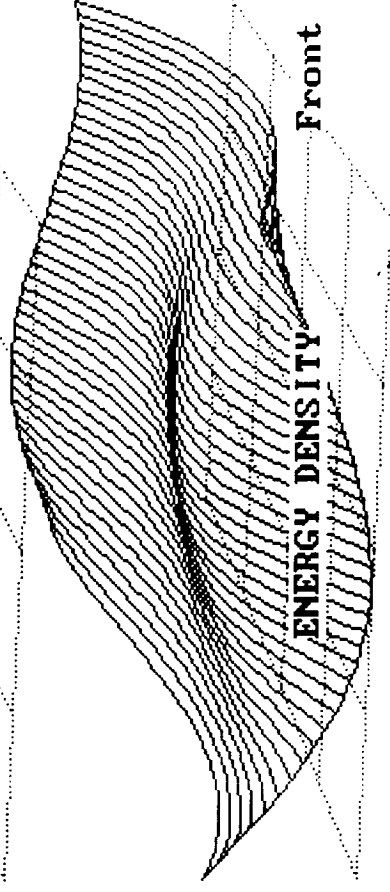
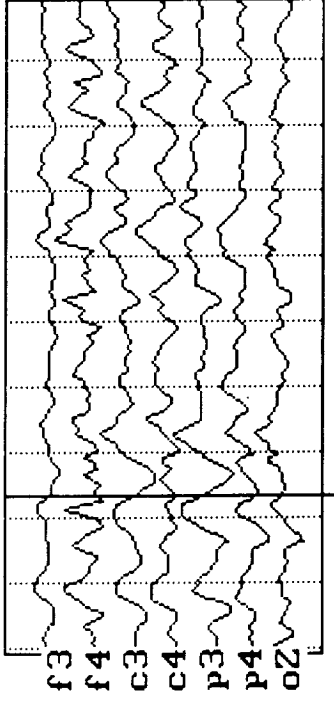
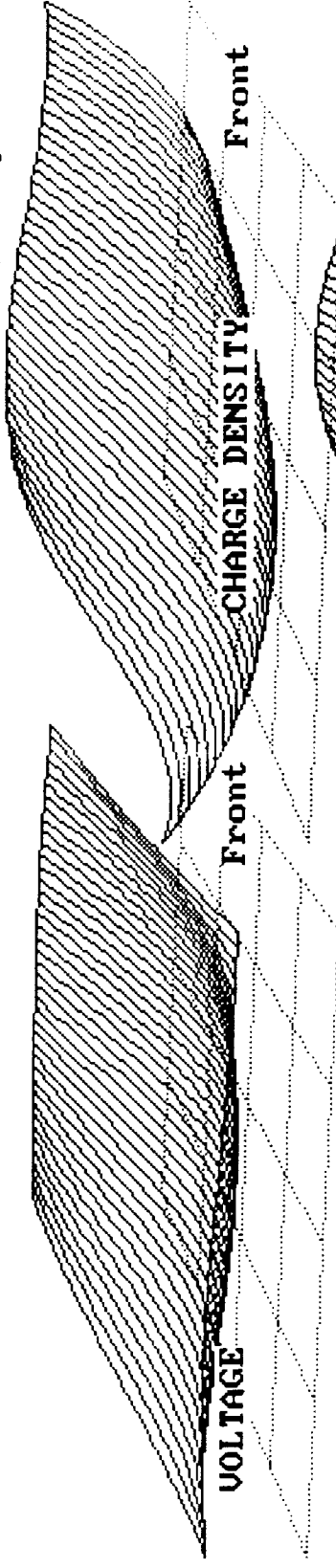
$$V = (a + bX + cY + dXY)^3$$

$$V = (b_1 + b_2X + b_3X^2 + \dots + b_{15}X^2Y^3 + b_{16}X^3Y^3)$$

Derivation of EEG Energy Density Surface

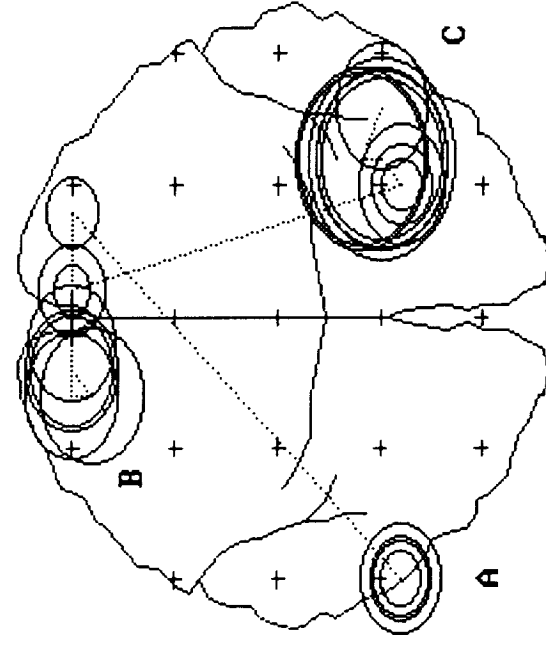
$$\phi(x,y)$$

$$\rho(x,y) = -\epsilon \nabla^2 \phi(x,y)$$

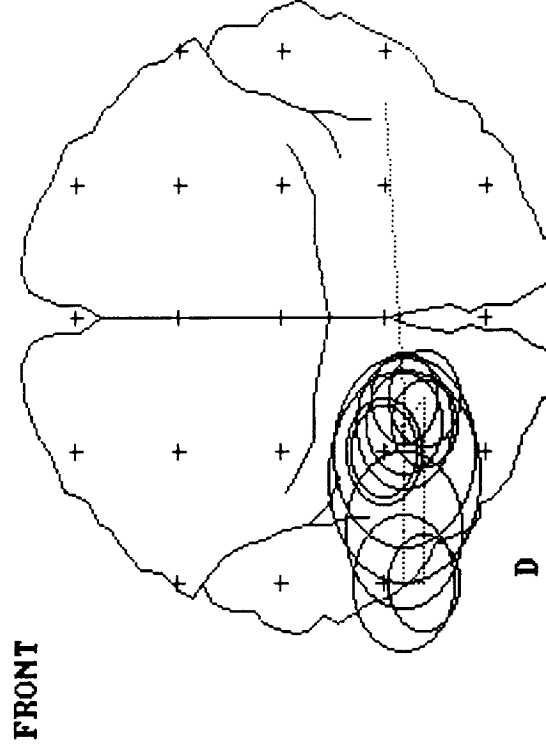


$$U = -\epsilon \phi \nabla^2 \phi.$$

Average Maxima of Measured Energy Density



0-300 MSEC.



300-600 MSEC.

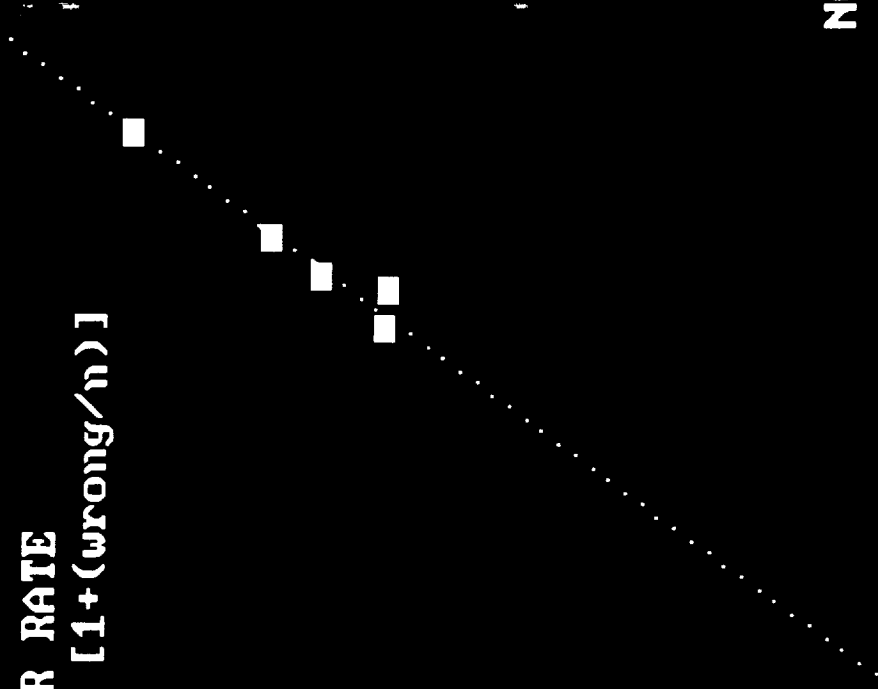
Task Error Index vs. Energy Density

$$\text{Index} = RT \times (1 + \text{wrong} / n)$$

<u>Electrode</u>	<u>Period (ms)</u>	<u>r²</u>	<u>Slope T</u>
T5	47-86	0.913	-5.624
T5	55-94	0.948	-7.402
FPZ	86-126	0.877	-4.624
FPZ	94-133	0.897	-5.122
F3	102-141	0.878	-4.639
FPZ	110-149	0.856	-4.609
FPZ	118-157	0.876	-4.223
P4	141-180	0.851	4.134
P4	149-188	0.878	4.657
P4	157-196	0.882	4.740
P4	165-204	0.869	4.458
T5	172-211	0.914	-5.637

Group Performance vs. Energy Density

ERROR RATE
= $rt [1 + (wrong/n)]$



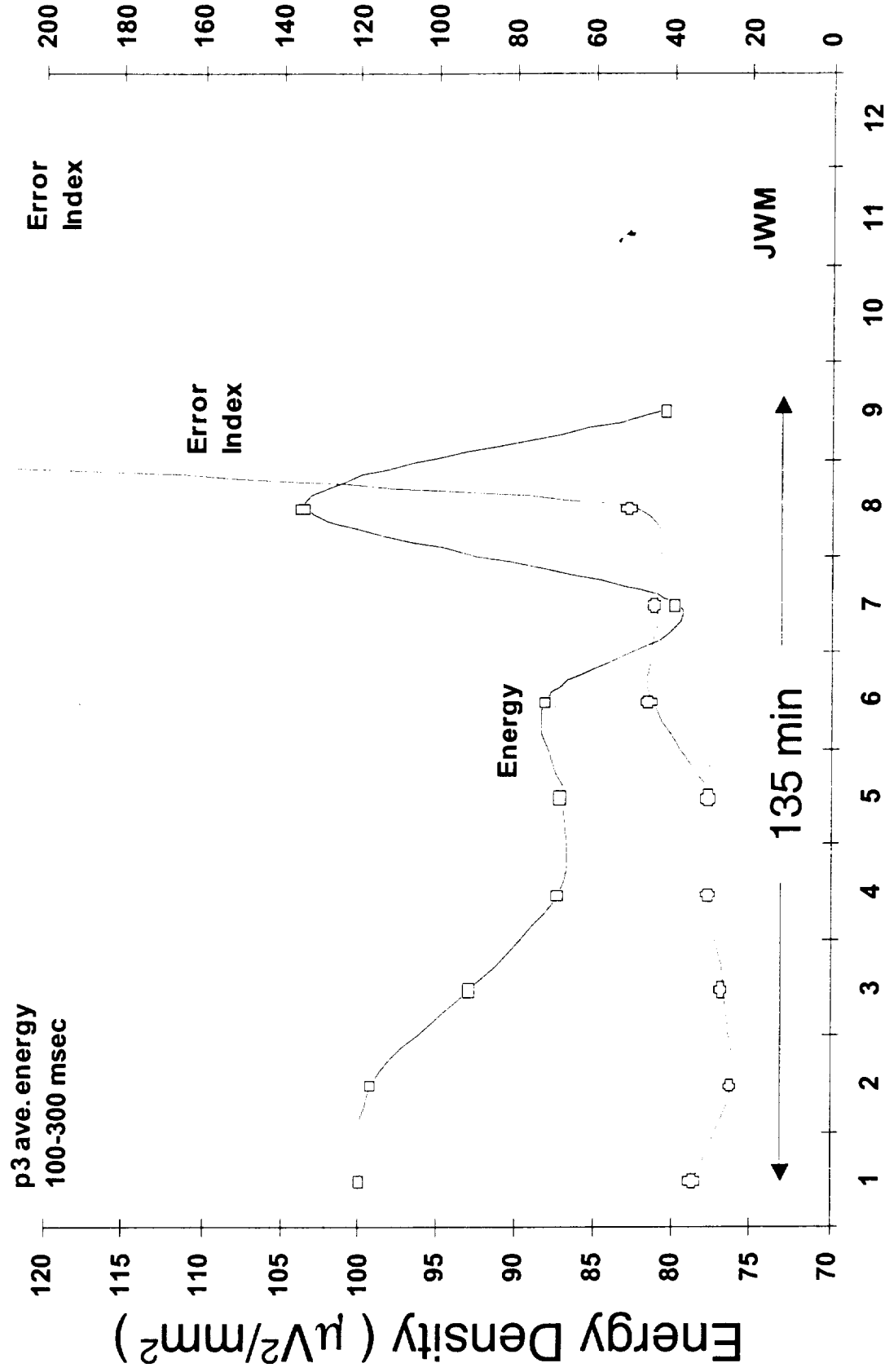
R-SQUARE = 0.957
INTERCEPT = -11.476
SLOPE = 0.0942
SLOPE STD = 0.012
SLOPE T = 8.14

SITE: C4, right center
PERIOD: 196- 235 msec.

NORMALIZED ERP AMPLITUDE

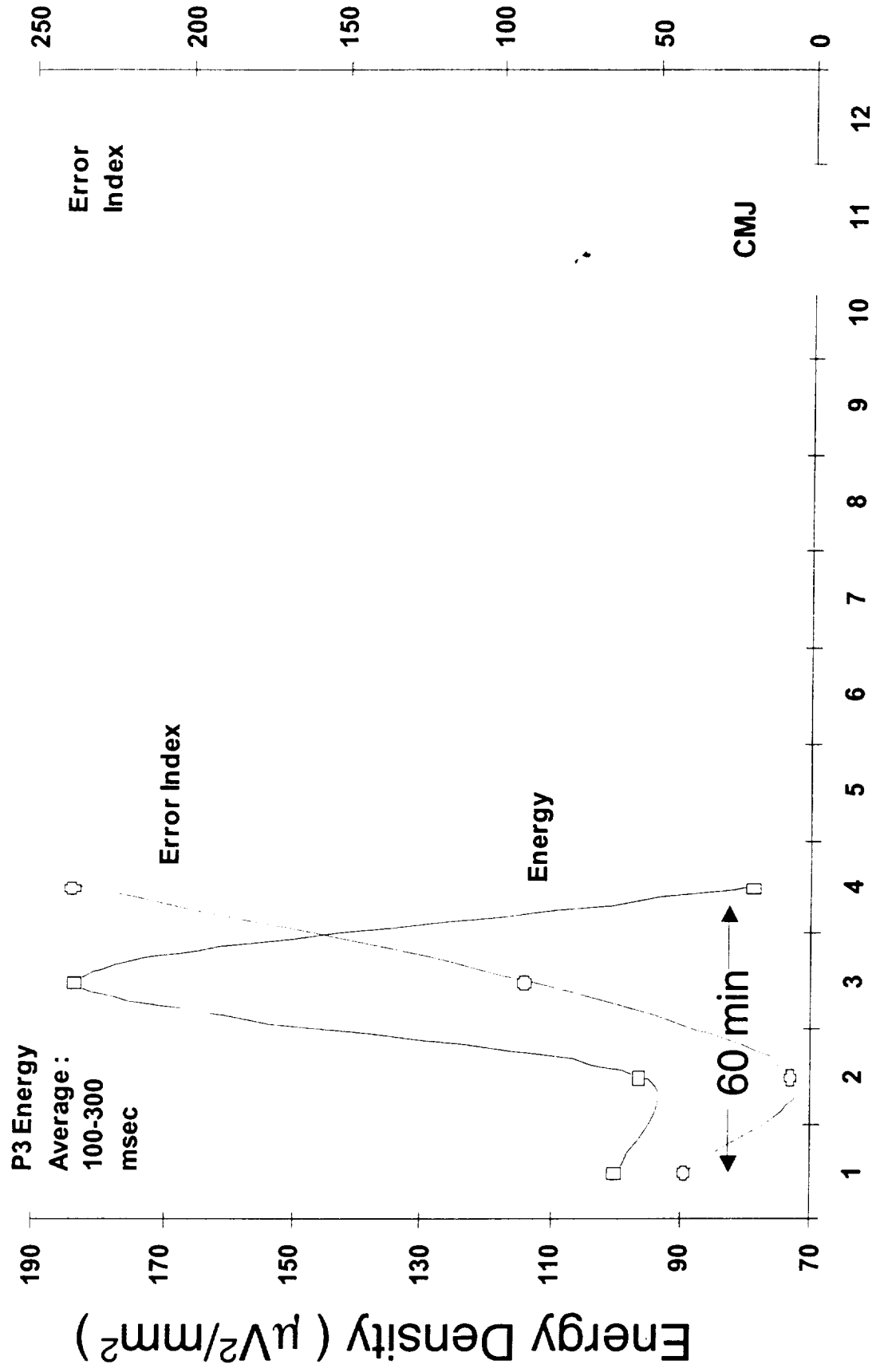
Performance & Energy Density Over Time

Normal Subject



Performance & Energy Density Over Time

Subject Who Reported Feeling Sick



Future Plans

Improve Spatial and Computational Resolution

- 64 electrodes (128 electrodes in some subjects)
- Spline Laplacian (Nunez)
- Separate estimates of radial (gyral) and tangential (sulcal) current source densities
- Comparison of Montgomery's energy density with CSD and potential measures

Addition of irrelevant auditory probe

- Low level aperiodic random tone series
- Individual calibration
- Analysis of performance-related ERP component changes

Irrelevant Probe ERPs and Mental Effort

Electronic Warfare Simulation
(Kramer, Trejo & Humphrey, 1996)

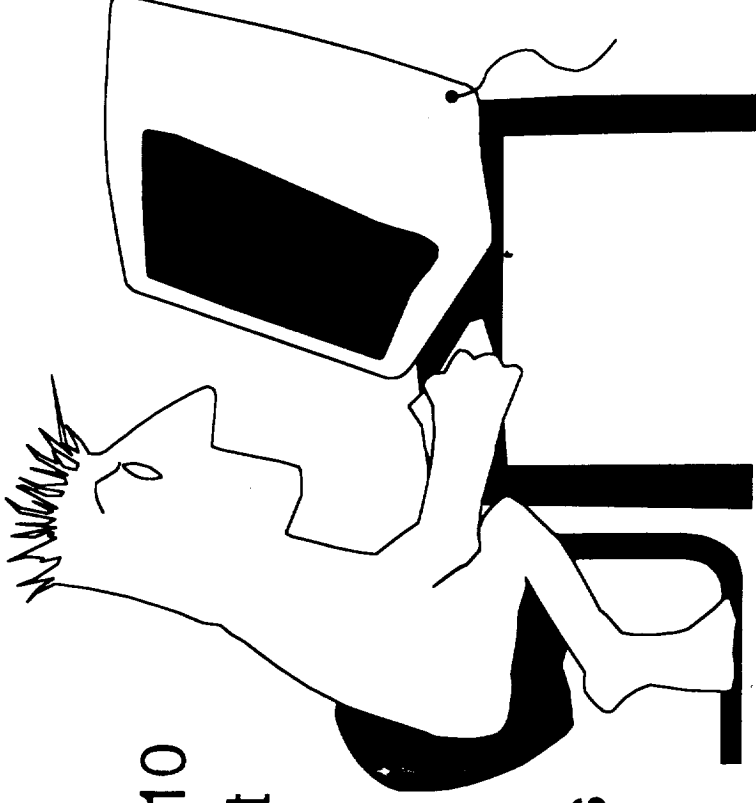
10 experienced EWs

Baseline task

- Auditory oddball 80/10/10
- Respond to one deviant tone

1-hr mission scenario

- Realistic Simulation
- Auditory oddball probes
- Variable target density over time



ERP Results with Probe Stimuli

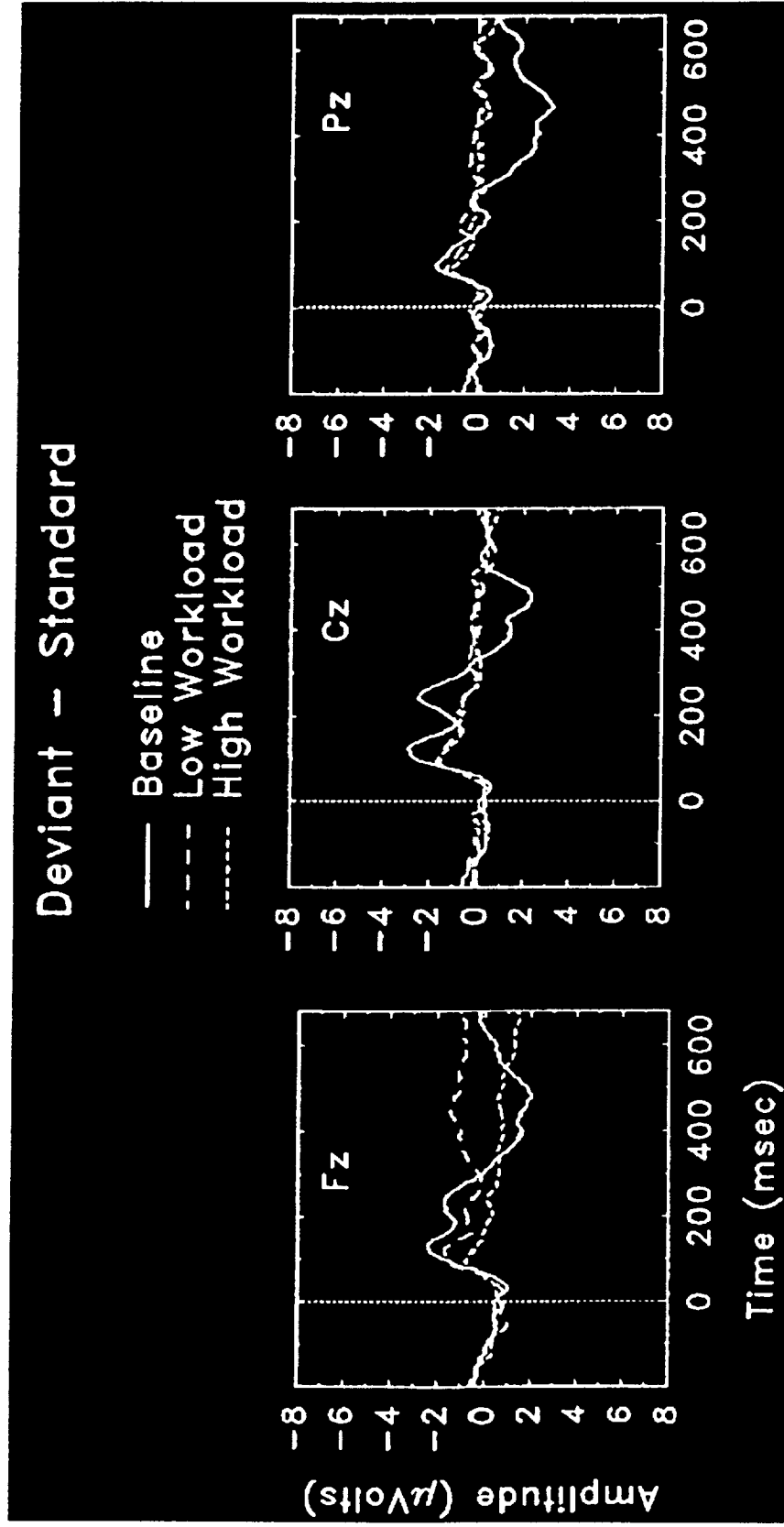


FIG. 7.5. Grand average waveforms derived by subtracting the ERPs elicited by the standard tones (e.g. the tones which occurred on 80% of the tone trials) from the ERPs elicited by the deviant tones.

Summary of Results with Probe Stimuli

Baseline task

Deviant tones

- Large N1, N2
- P3 elicited only by target deviants

Deviant vs. standard

- Mismatch negativity for both deviants

EW Simulation

Standard tones

- Reduced N1, N2

Deviant tones

- No P300
- Reduced N1, N2
- Reduced MMN

Both tone types

- Reductions covary with scenario complexity

Conclusions and Recommendations

Energy Density

- Initial data show potential onset of cognitive fatigue
- Confirm results with high-resolution source imaging and modeling, and ERP component analysis

Probe ERPs

- Prior data show tracking of mental workload
- Extend application to monitoring of cognitive fatigue
- Combine probes with mental math task and source imaging



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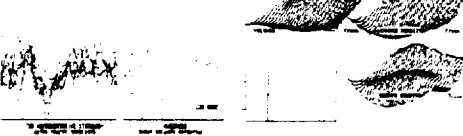
Motivation



In today's world, we are increasingly faced with a variety of tasks that require sustained attention. As the demands on our cognitive resources increase, the risk of mental fatigue increases. Mental fatigue is a state of reduced cognitive performance that is caused by prolonged periods of intense mental activity, stress, fatigue, and distraction. Any one of these can eventually lead to performance errors.

It would be desirable to predict deterioration in an individual's performance of demanding cognitive tasks. Furthermore, performance level actually starts to change. The necessary level of alertness to detect such changes is not always clear. The result is that we need significant performance deterioration on individual tasks if the risk is not through more effort, to maintain an adequate level of performance for a time.

Theory



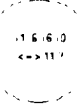
The time-varying field (or flux) is used to relate potentials measured on the scalp to underlying physiological processes. Errors have occurred in the past in the use of these measures, if the voltage is not from a single electrode, the use of a waveform transformation. Energy density as defined here may provide the connection between scalp potentials and physiological effort.

An event-related potential (ERP) is the averaged scalp voltage potential of a particular scalp location that is generated in response to a variety of time stimuli (see photo above). With multichannel ERP data, we can generate a voltage map at each sample time. From the voltage map, we can calculate energy density maps. The process of voltage maps change density is potential energy density (see photo above).

$$E(x,y) = (x,y)p(x,y) = \frac{1}{2} \epsilon(x,y) \nabla^2(x,y)$$

Multichannel data permits us to calculate energy density at each sampled time. Are the units of energy more meaningful than voltage? Can energy be related to performance during long duration tasks? During our first year, we refined our experimental procedures to permit us to measure performance and energy density over extended task durations.

Subjects are given an exhausting course of arithmetic problems to perform (see photo to left). They must respond using a keypad. Scalp voltages from 80 to 100 electrodes (about 8-14 minutes of elapsed time) are sampled over ERP. We collected over 1000 samples. We continued to take data until the subject stated they could no longer continue. Our most dedicated subject performed about 1000 problems over a period of 3 hours. We are looking for changes in performance over the test period, and for changes in energy density (ERP) over the same time period.



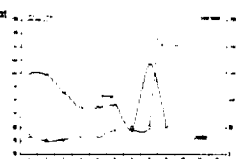
Experimental Methods & Results



The figure at right illustrates the typical performance and neural activity response that we observed. We found a consistent relationship across most subjects.

The data represents the output of a neural network. As subjects' performance deteriorates from activity during the final ERP (just before they reached exhaustion), the neural network pattern was found to be consistent across subjects who performed well. Thus, we found performance to be a very poor predictor of exhaustion.

The neural network energy density at 3 (see the left graph) gives the mathematical processing center in the left hemisphere. Energy density generally decreased with time, and exhibited a peak and sharp decline just prior to the exhaustion. This behavior is apparent in subjects who tested for different time periods. Subject 1 below, was sleep deprived and reached exhaustion very quickly. Subject 2 performed the task for 2.5 hours. Subject 3 for 3 hours.



The evolution of the EEG pattern during the task time can be explained in terms of the rising cost of maintaining metabolic energy resources from other maintenance type or homeostatic brain activities in order to sustain concentration on the mental arithmetic task at hand. If the cost of keeping these maintenance activities is cumulative, it is logical to expect the brain to eventually reduce the state of energy resources (reflected in the response) to preserve them. Thus the subject will also show a decrease in energy level in maintenance activities at the expense of the arithmetic task, and the individual's performance will decline rapidly.

A simple mathematical model can be used to illustrate such a resource allocation process as illustrated below.

Proposed Model

M (maximum allocation rate to mental arithmetic) is a maximum of maximum difference, fully available as H (allocation rate to homeostasis).

$$M = H - N$$

Homeostatic neglect (NH) is a function of the required task, expressed as:

$$NH = (H - M) \cdot dt$$

Mental arithmetic neglect (NM) is simply the shortfall relative to required rate.

$$NM = H - M$$

The homeostatic resource flow is regulated to balance the neglected functions.

$$dM/dt = 2 \cdot (NM - NH)$$

These equations simplify the system to one model that can be solved numerically, which in operator notation becomes:

$$D^2 M + D M = 2 \cdot (NM - NH)$$

With parameter (e.g., RM, RM) fitting, the model was used to simulate the experimental workman's cognitive data of the three subjects shown earlier. As shown below, we were able to reproduce the trends of responses of each individual subject using the model. The experimental data is given as the solid line and the model fit is given as the dashed line. The model fit is very close to the experimental data. The two traces in each figure are intentionally accelerated to provide a better comparison of the actual and simulated activity.



Summary

This study demonstrates that the energy density analysis of long-term ERP may be used to develop a model that reproduces individual subject's activity, with limited arithmetic task performance. A predictive ERP model was derived which may provide insight into the effects of a number of factors on individual subject's performance. A resource allocation model was developed that can be used to explain the cognitive processing that may take place during long-term task performance.

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For additional information please contact Leslie D. Montgomery Tel: 650-407-0174, E-Mail: montgomery@nasa.gov

Suggested Reading

- R. W. Montgomery, L. D. Montgomery, and R. Guisado: "Cortical localization of cognitive function by regression of performance on event-related potentials." *Aviat. Space Environ. Med.* 62, 110-124 (1991).
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- L. D. Montgomery, R. W. Montgomery, and R. Guisado: "Continuous monitoring of cerebral blood flow: Correlation of mesencephalographic activity during cognition." *Journal of Clinical Engineering* 18(3), 235-244 (1993).
- L. D. Montgomery and R. Guisado: "Mesencephalographic and electroencephalographic measures of cognitive workload: Analytical procedures." *Biological Psychology* 40, 1-15 (1995).